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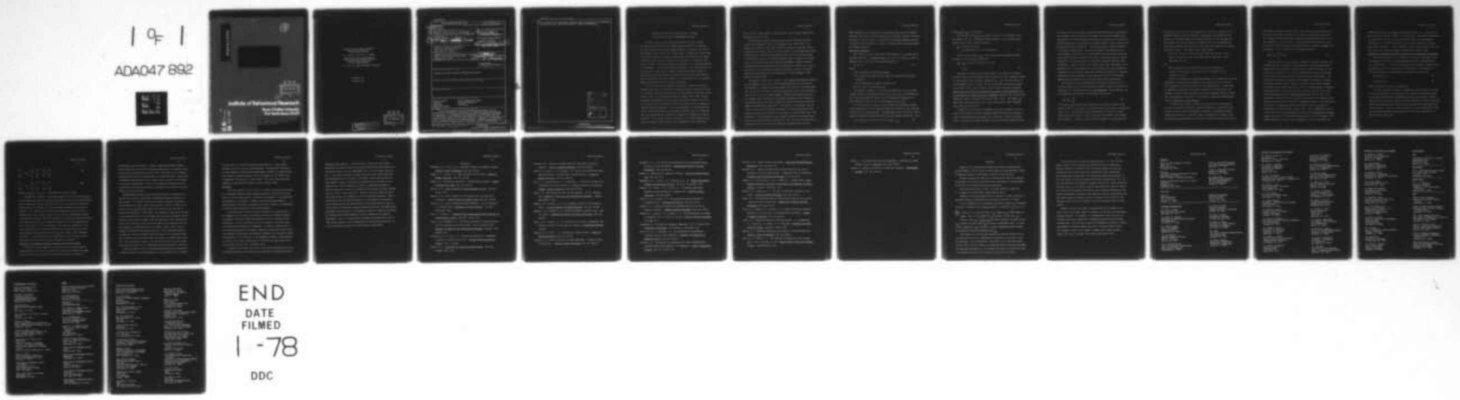

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Moderator Analysis Based on Subgrouping:
Problems Arising from the use
of Standardized Variables

L. R. James, K. E. Coray, & R. G. Demaree

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The use of parameters based on standardized variables, such as correlation coefficients or beta-weights, in subgrouping moderator analysis is addressed. It is suggested that a comparison of correlation coefficients or beta-weights across different populations may lead to results that are erroneous with respect to true causal processes. Moreover, it is proposed that even in descriptive analyses parameters based on standardized data may vary across populations simply because of population specific idiosyncracies. It
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is recommended that subgrouping moderator analysis be based on unstandardized data and that more attention be given to causal considerations.

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Moderator Analysis Based on Subgrouping: Problems
Arising from the Use of Standardized Variables

In recent years, research involving moderators has had a somewhat equivocal role in industrial and organizational psychology (cf. Abrahams & Alf, 1972; Dunnette, 1972; Gross, Faggan-Streckler, & McCarthy, 1974; Guion, 1976; McNemar, 1969; Pinder, 1973; Zedeck, 1971). Nevertheless, various forms of moderator analysis are currently quite popular as evidenced by the number of studies in which they have recently been employed, not to mention their role in a number of current theoretical perspectives (e.g., path-goal theories of leadership). It is somewhat surprising, therefore, that more attention has not been paid to some inherent problems in applying moderator analysis to naturally occuring "field" data, particularily since many of these problems have been addressed (see above references). As discussed here, one currently popular approach may lead to erroneous conclusions.

Two of the most popular appoaches for moderator analysis on naturally occuring field data are (a) moderated regression, which is based on the logic of the general linear model and involves the computation of interaction (cross-product) terms in a regression equation (cf. Cohen & Cohen, 1975); and (b) moderation by subgrouping, where a sample is divided according to scores on one variable and then correlations among other variables in each subgroup are compared across the subgroups. In the latter approach, if the correlations between the same variables are significantly different across the subgroups, then the variable employed originally to identify the subgroups is termed a moderator. Recent examples of this procedure or its variants include Glenn, Taylor, and Weaver (1977), Kissler (1977), MacEachron (1977), Steers and

Spencer (1977), Stone, Mowday, and Porter (1977), and reviews by Boehm (1977) and Katzell and Dyer (1977).

The moderated regression approach has come under increasing criticism recently (cf. Darlington & Rom, 1972; Sockloff, 1976a, 1976b, 1977). For example, many research reports and a number of statistical texts have failed to differentiate between fixed versus random models; this oversight has serious implications for distributional assumptions and even for the appropriateness of the moderated regression approach (Sockloff, 1976a). Moreover, the assumptions of the general linear model, based on experimental designs involving randomization and orthogonality among the independent variables due to equal cell sizes, do not necessarily extrapolate directly to naturally occurring field situations lacking such characteristics (cf. Cook & Campbell, 1976; Overall & Spiegel, 1969).

The subject of this report, however, is the subgrouping moderator approach, and the argument is that a test of the difference between two correlations, each computed in a subgroup originally formed from scores on a presumed moderator, may lead to an erroneous conclusion regarding the import of the moderator. That is, for two or more subgroup samples, the causal relationships between two variables may be the same in the underlying populations even though the correlations between these same variables may differ significantly across the subgroup samples <u>and</u> the populations. The reason for this possible state of events is that the correlation is susceptible to sample and population idiosyncracies that may be of little or no importance to general causal laws. The rationale for this statement, and the argument presented, is developed below under the heading "theoretical assumptions". The theoretical assumptions are developed for causal or structural equations and populations in general.

These assumptions are then applied to populations identified by a potential moderator, where again structural equations are employed. Finally, the developed logic is shown to apply to "descriptive" subgrouping moderator analysis in which no causal assumptions are made. Population terms are again employed for exemplary purposes.

Theoretical Assumptions

With respect to causal (structural) relationships, it is assumed that a population variable x, in deviation form, is a cause for variable y, also in deviation form. The causal or structural equation is

$$y = b\,x + d \tag{1}$$

where:

y is the dependent, endogenous variable,

b is a partial regression weight as well as a population structural parameter,

x is the independent, exogenous variable, and

d is the error or disturbance term.

For exemplary purposes, it will also be assumed that (a) x and y have neither random nor nonrandom measurement error; (b) x is not correlated with d; (c) the relationship is linear; (d) the variables were measured on at least interval scales; and (e) d is distributed as $N\ (0,\ \sigma_d^{\ 2})$.

It is instructive to explain how the variances and covariances among various components of the structural equation are determined. The population variance for x is designated $\sigma_x^{\ 2}$. The population variance for y may be ascertained by multiplying through equation 1 by y and taking expectations. That is

$$\sigma_y^{\ 2} = E\ (y\ y) = b\ E\ (y\ x) + E\ (y\ d) = b\ \sigma_{yx} + \sigma_{yd} \tag{2}$$

where σ_{yx} and σ_{yd} are covariances.

The covariance term σ_{yd} can be shown to be equal to the variance of the disturbance term, σ_d^2. Multiplying through equation 1 by d and taking expectations results in the following identity.

$$\begin{aligned}\sigma_{yd} &= b\,E\,(x\,d) + E\,(d\,d)\\ &= \sigma_d^2 \text{ because } E\,(x\,d) = 0 \text{ by assumption.}\end{aligned} \tag{3}$$

Finally, the covariance, σ_{yx}, can be determined by multiplying through equation 1 by x and taking expectations.

$$\begin{aligned}\sigma_{yx} &= \sigma_{xy} + E\,(x\,y) = b\,E\,(x\,x) + E\,(x\,d)\\ &= b\,\sigma_x^2\end{aligned} \tag{4}$$

Examination of equations 2 through 4 leads to the important conclusion that the variances and covariances are all functions of three components, namely: (1) the variance of the exogenous variable x (i.e., σ_x^2), (2) the variance of the disturbance term (i.e., σ_d^2), and (3) the population structural parameter b (cf. Duncan, 1975, p. 55). Further, and of crucial importance, <u>it can be assumed that any of these three components may change across populations without necessitating a change in the other components</u> (Blalock, 1967; Duncan, 1975; Namboodiri, Carter, & Blalock, 1975; Wiley & Wiley, 1971). For example, σ_x^2 might differ among populations (e.g., male versus female) without requiring that b and σ_d^2 be different.[1]

However, if any of the three components (σ_x^2, σ_d^2, b) differs as a function of the populations studied, parameters based on standardized variables such as correlations and beta-weights will, in general, also differ (Duncan, 1975). In structural equation analysis, this is particularily salient because

it raises the issue of whether standardized (within population) or unstandardized variables should be employed to determine the structural parameters for each population (in random samples from different populations, the question is whether standardized or unstandardized variables should be used to estimate the population structural parameters). Structural equation analysis is designed to investigate general causal laws and this suggests that population structural parameters should be based on coefficients with the greatest likelihood of invariance across populations rather than on coefficients that are heavily influenced by the idiosyncracies of a particular population (Blalock, 1967). Accordingly, a number of authors (cf. Blalock, 1964, 1967, 1968; Duncan, 1975; Namboodiri et al., 1975; Spaeth, 1975; Wiley & Wiley, 1971) have recommended (strongly) the use of partial regression coefficients (b-weights) to represent population structural parameters, especially when tests of the differences among structural parameters are to be made among different populations.

The rationale for the recommendation of b-weights recognizes the fact that beta-weights are based on standardized variables, which by definition are adjusted by the standard deviations in each population. More explicitly, the beta-weight (β) is related to the b-weight by the equation

$$\beta_{yx} = b_{yx} \frac{\sigma_x}{\sigma_y} \qquad (5)$$

If the ratio σ_x/σ_y differs among populations, then the beta-weight is also likely to differ. For example, as discussed above, σ_x^2 may differ among populations (e.g., one population is more heterogeneous), thereby very likely affecting the beta-weights. However, also as discussed above, the b-weight may not differ. It cannot be stated that the b-weight will not change (see

Footnote 1), but only that the beta-weight is more likely to change (i.e., be population specific) than the b-weight. Consequently, the b-weight is more likely to be invariant across populations and therefore it is concluded that the b-weight is the better indicator of general causal laws or hypothetical structural parameters that generalize to more than one population (cf. Blalock, 1967; Tukey, 1964).[2] For example, Tukey (1964) stated:

> We are sure that the correlation cannot remain the same over a wide range of situations, but it is possible that the regression coefficient might (p. 41).

and

> Thus it seems to me that analyses in terms of causation are usually more appropriately stated in terms of regression than of correlation (p. 41).

A critical corollary of the preceding argument is that population structural parameters, as determined by b-weights in each population, may be invariant across populations while beta-weights may vary significantly. In other words, in comparisons of population structural parameters across populations, the b-weight, rather than the beta-weight, is the more meaningful basis for comparison; the b-weight is less likely to be affected by population idiosyncracies that have nothing to do with causality.

It follows directly that comparison of beta-weights across populations may lead to erroneous conclusions regarding differences or similarities with respect to general causal relationships. Examples of erroneous conclusions resulting from the use of statistics based on standardized variables to test differences among populations are provided by Schoenberg (1972), Spaeth (1975),

Tukey (1964), and Wiley and Wiley (1971). The same conclusion applies to the zero-order correlation coefficient. The zero-order correlation coefficient is, in general, similarly affected by population differences in any one of the three components, σ_x^2, σ_d^2, and b, is based on standardized variables, and, in bivariate structural equations using standardized variables, is _equal_ to the beta-weight. This is reflected by the following equation.

$$\beta_{yx} = b_{yx} \frac{\sigma_x}{\sigma_y} = r_{yx} \tag{6}$$

Given the equality of β_{yx} and r_{yx} in bivariate structural equations, the position developed, favoring the use of _b_-weights rather than beta-weights, suggests that the correlation coefficient may be a fallible indicator of the actual causal relationships. In effect, the difference between the _b_-weight and the correlation coefficient may be viewed in the following manner. The _b_-weight is a measure of the slope of the regression line when the variables retain their original metric. Thus, _b_ in equation 1 measures the _concrete_ contribution that _x_ makes directly to _y_, and, if the _same metrics_ are employed across populations, the contribution that _x_ makes directly to _y_ can be compared among populations in an _absolute sense_ (Wright, 1960, p. 192). The correlation coefficient is also a measure of the slope of the regression line; however, the correlation coefficient is an _abstract_ measure of the slope because it is based on an _abstract scale_ that varies as a function of σ_x/σ_y (i.e., standardized variables) (Wright, 1960, p. 194). Thus, a comparison of correlation coefficients among populations is in actuality _a comparison of abstract scales_, each adjusted for population idiosyncracies by the ratio σ_x/σ_y. It is somewhat obvious, therefore, that the _concrete_ contribution (_b_-weight) may

remain invariant while the _abstract_ contribution (_r_) may vary. This is one of the major reasons why Tukey (1964, p. 39) noted that " 'correlation coefficients are justified in two and only two circumstances, when they are regression coefficients, or when the measurement of one or both variables on a determinate scale is hopeless' ". (This statement is perhaps overly strong for the use of correlational approaches _within_ a population [cf. Wright, 1960]).

Examination of Subgrouping Moderator Analyses from the Standpoint of Causality

For exemplary purposes, it is assumed that a potential moderator "_Z_" has been employed to separate a disparate population into two (sub)populations (e.g., male-female). It is also assumed that a causal model is available which *specifies that X is the cause for Y in each population*. For example, the structural equations in each population, in deviation form, would be

$$y_1 = b_1 x_1 + d_1 \tag{7}$$

$$y_2 = b_2 x_2 + d_2 \tag{8}$$

where the subscript refers to the population.

The salient question is whether the underlying causal process is the same in the two populations. This question can be tested by ascertaining whether the two population structural parameters, b_1 and b_2, are the same. Based on developed logic, the two _b_-weights are the most appropriate basis for comparing the causal processes because they may remain invariant even though σ_x^2 or σ_d^2 may be different. However, to make the point from another perspective, if the scores in each population were standardized, the following structural (or path) equations would ensue

$$\frac{y_1}{\sigma_{y_1}} = b_1 \frac{\sigma_{x_1}}{\sigma_{y_1}} \frac{x_1}{\sigma_{x_1}} + \frac{\sigma_{d_1}}{\sigma_{y_1}} \frac{d_1}{\sigma_{d_1}} \qquad (9)$$

$$\frac{y_2}{\sigma_{y_2}} = b_2 \frac{\sigma_{x_2}}{\sigma_{y_2}} \frac{x_2}{\sigma_{x_2}} + \frac{\sigma_{d_2}}{\sigma_{y_2}} \frac{d_2}{\sigma_{d_2}} \qquad (10)$$

where $b_i\ (\sigma_{x_i}/\sigma_{y_i}) = \beta_i = r_i$ = a path coefficient (Duncan, 1975).

A comparison of equations 7 and 8 with equations 9 and 10 illustrates again why the beta-weights and the correlation coefficients (and the path coefficients) are, in comparison to the b_i, more likely to vary as a function of population idiosyncracies and therefore to provide erroneous conclusions with respect to causality. The reasons for the population idiosyncracies may be intrinsic to the populations (e.g., larger variance in one of the two populations, different developmental backgrounds, different exposure to environmental stimuli, different causal processes affecting the exogenous variable [but not the endogenous variable], and so forth). On the other hand, if the moderator variable Z is related to either X or Y, then the differences in the correlations may be statistical artifacts (which applies also to the b_i) (cf. McNemar, 1969; Abrahams & Alf, 1972). In this situation, it is likely that the causal process has been misspecified and Z should not have been employed as a moderator.[3]

Examination of Subgrouping Moderator Analysis for Descriptive Studies

The discussion above suggests that comparisons of the causal processes among populations should not be predicated on population parameters (or sample statistics) that used standardized variables (beta-weights, correlation

coefficients, path coefficients). However, subgrouping moderator analyses based on naturally occurring field data and comparisons of correlation coefficients are not typically cast in causal terms. This makes not the slightest difference when, based on developed logic, it is possible that a comparison of correlation coefficients may lead to results that are contrary to the causal or structural relationships. That is, the correlation coefficients may be significantly different simply because of population idiosyncracies that have nothing to do with causality.

Disregarding structural equations and their rigorous assumptions, the sole use of correlation coefficients in subgrouping moderator analysis is again suspect. For example, using only descriptive analyses and allowing random measurement errors in the variables (which attenuate $\underline{b}$-weights in the bivariate case), $\underline{\tilde{b}_1}$ and $\underline{\tilde{b}_2}$ ($\underline{\tilde{b}_1}$ connotes the coefficients are not used as structural parameters), or the slopes of the regression lines, may be the same in two populations while the beta-weights and correlation coefficients differ. Similarly, the errors of estimate, which are analogous to the standard deviations of the disturbance terms, may be the same in two populations while the beta-weights or correlations differ (cf. McNemar, 1969). Thus, the beta-weights or correlations may differ across two or more populations formed on the basis of a potential moderator while the slopes of the regression lines, in the absolute sense discussed earlier, and errors of estimate remain invariant. This conclusion is based on the same logic employed in the discussion of structural equations (i.e., standardized versus unstandardized variables).

Given the inherent faults of employing parameters based on standardized variables to test population differences, it is recommended that the conduct

of such tests in the future be predicated on parameters, or their sample estimates, that do not involve standardization. The appropriate information for each population (sample) would include means, variances or standard deviations, partial regression weights, errors of estimate (or "hit rates") and, if appropriate, intercepts (cf. Guion, 1976).[4] The size of the populations (samples) is also important (Schmidt, Berner, & Hunter, 1973).

Conclusion

It has been suggested that a reliance on testing correlation coefficients in a subgrouping moderator analysis design may provide results that are contrary to the underlying causal or structural relationships. A straightforward recommendation is, therefore, to begin to replace subgrouping moderator analyses based on descriptive paradigms with the more rigorous, and meaningful, structural equation approaches (but not path analysis).

In situations where structural equation analysis is not appropriate, it was suggested that correlation coefficients may again be fallible indicators of meaningful differences among relationships of the same variables across populations. In these situations, the use of parameters (statistics) based on unstandardized variables was recommended. In addition, questions such as the original population (total sample) covariances between the potential moderator and both the independent and dependent variables, the reliability (errors of measurement) of the variables in each population (sample), cross-validation of results, the practical significance of any differences which might exist, and so forth are salient (cf. Schoenberg, 1972).

It should be noted that even with all of the above examinations and tests, the subgrouping moderator analysis based on descriptive paradigms may provide

misleading interpretations. Critical factors in causal analysis include assumptions and empirical tests of the causal sequencing of the variables and the specifications of causal relationships (e.g., recursive versus nonrecursive). Any study which fails to address these issues may report significant but nevertheless erroneous results. This issue is particularly salient for those studies in which a causal model is proposed and yet the data are not analyzed from a causal standpoint, or where an *experimental paradigm* is employed which fails to take into consideration such things as causal feedback loops (cf. James & Singh, in press). (There is no need to single out particular authors here; the problems are both well known and widespread. What is surprising is that the problems continue to be well known and widespread). Causal sequencing and other specifications of structural models are particularilarly salient for moderator variables because not only must the nonadditivity assumption be justified (e.g., the moderator is neither a cause nor an effect), but serious identification problems can result (especially in moderated regression). Thus, it is likely that investigators will become more circumspect about proposing a host of moderators as research begins (hopefully) to replace descriptive analyses with well-specified causal models.

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Requests for reprints should be sent to Lawrence R. James, Institute of Behavioral Research, Texas Christian University, Fort Worth, TX 76129.

[1]It is recognized that the population structural parameter $\underline{b}$ is typically estimated by ordinary least squares, making it a function of σ_x^2 (i.e., $\underline{b} = \frac{\sigma_{xy}}{\sigma_x^2}$). However, it is also true that if σ_x^2 changes, σ_{xy} is also likely to change. Thus, it is possible for σ_x^2 to change, but not $\underline{b}$ (or σ_d^2).

[2]The fact that $b_{yx} = (\sigma_y/\sigma_x)\ \beta_{yx}$ has little relevance; the point is that b_{yx} is based on raw data while β_{yx} is based on standardized data. Or, from another perspective, β_{yx} is based on a linear transformation that involves more population specific information than b_{yx}.

[3]For example, if $\underline{Z}$ is linearly related to $\underline{X}$, then the variance of $\underline{X}$ in the populations defined by subgrouping on $\underline{Z}$ may vary as a function of the partitioning of the $\underline{Z}$ distribution. This should not be construed to mean, however, that $\underline{X}$ must be related to $\underline{Z}$ before the variance in $\underline{X}$ will vary among the populations defined by $\underline{Z}$. For example, the mean for $\underline{X}$ could be the same in each population and yet the variances for $\underline{X}$ could still differ.

[4] It is instructive to review the study by Stone et al. (1977) in this regard. Briefly, this study was descriptive and involved a subgrouping moderator analysis to ascertain if the correlation between job scope and satisfaction with the work itself was moderated by need for achievement (three subgroups were employed). The results were significant; however, in the total sample need for achievement was correlated significantly (.28, .42) with the independent and dependent variables, respectively. Based on implicit selection theory, it is therefore possible that selection on need for achievement affected differentially the variances and correlations between the independent and dependent variables in each subgroup. However, no information was given with respect to variances, errors of estimate, and so forth for each subgroup, and thus it is not possible to sort out potential reasons for the results.

Failure to report what might be important data is not limited to the Stone et al. (1977) study; rather, it appears to be the norm for subgrouping moderator analyses. For example, in a nonexhaustive review of recent job attribute studies that employed the subgrouping moderator analyses design discussed here, not one article reported the information necessary to compute unstandardized regression weights and errors of estimate (Aldag & Brief, 1975; Hackman & Lawler, 1971; Hackman & Oldham, 1976; Oldham, Hackman, & Pearce, 1976; Sims & Szilagyi, 1976; Stone, 1976; Wanous, 1974).

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Research Psychologist
ONR Branch Office
536 S. Clark St.
Chicago, IL 60605

Principal Investigators

Dr. Alvin J. Abrams
Navy Personnel R & D Center
San Diego, CA 92152

Dr. Clayton P. Alderfer
Department of Administrative Sciences
Yale University
New Haven, CT 06520

Dr. James A. Bayton
Dept. of Psychology
Howard University
Washington, DC 20001

Dr. Carl Bennett
Battelle Memorial Institute
4000 N.E. 41st St.
Seattle, WA 98105

Dr. H. Russell Bernard
Dept. of Sociology & Anthropology
West Virginia University
Morgantown, WV 26506

Dr. Milton R. Blood
School of Business
Georgia Institute of Technology
Atlanta, GA 30332

Dr. Davis B. Bobrow
University of Maryland
College Park, MD 20742

Dr. David G. Bowers
Institute for Social Research
University of Michigan
Ann Arbor, MI 48106

Dr. Dynes
Ohio State University Research Found.
1314 Kinnear Road
Columbus, OH 43212

Dr. Fred E. Fiedler
Department of Psychology
University of Washington
Seattle, WA 98105

Principal Investigators (continued)

Dr. Allan H. Fisher, Jr.
Hay Associates
1625 Eye St., N.W. Suite 1001
Washington, DC 20006

Dr. Samuel L. Gaertner
Department of Psychology
University of Delaware
220 Wolf Hall
Newark, DE 19711

Dr. Paul S. Goodman
Graduate School of Industrial Admin.
Carneige-Mellon University, Schenley Park
Pittsburgh, PA 15213

Dr. Gloria L. Grace
System Development Corporation
2500 Colorado Ave.
Santa Monica, CA 90406

Dr. Eric Gunderson
Naval Health Research Center
San Diego, CA 92152

Dr. Richard Hackman
Department of Administrative Sciences
Yale University
New Haven, CT 06520

Dr. Thomas W. Harrell
Graduate School of Business
Stanford University
Stanford, CA 94305

Dr. Charles F. Hermann
Ohio State University Research Foundation
1314 Kinnear Road
Columbus, OH 43212

Dr. Charles L. Hulin
Department of Psychology
University of Illinois
Champaign, IL 61820

Dr. Norman J. Johnson
School of Urban & Public Affairs
Carnegie-Mellon University
Pittsburgh, PA 15213

Dr. David C. McClelland
McBer and Company
137 Newbury St.
Boston, MA 02139

Dr. Elliott M. McGinnies
Psychology Department
American University
Washington, DC 20016

Dr. Terence R. Mitchell
School of Business Administration
University of Washington
Seattle, WA 98195

Dr. Peter R. Monge
Dept. of Speech-Communication
California State University
San Jose, CA 95192

Dr. Stanley M. Nealey
Battelle Memorial Institute
4000 N.E. 41st St.
Seattle, WA 98105

Dr. Herbert R. Northrup
Industrial Research Unit
University of Pennsylvania
Philadelphia, PA 19174

Dr. Benson E. Penick
Carnegie-Mellon University
Margaret Morrison 410
Pittsburgh, PA 15213

Dr. Chester M. Pierce
Harvard University
Nichols House
Appian Way
Cambridge, MA 92138

Dr. Diane M. Ramsey-Klee
R-K Research & System Design
3947 Ridgemont Dr.
Malibu, CA 90265

Dr. Karlene H. Roberts
School of Business Administration
University of California
Berkeley, CA 94720

Dr. Moshe F. Rubinstein
University of California
405 Hilgard Ave.
Los Angeles, CA 90024

Dr. John Ruhe
University of North Carolina
Dept. of Business Administration
Charlotte, NC 28223

Principal Investigators (continued)

Dr. Rudolph J. Rummel
Political Science Department
University of Hawaii
Honolulu, HI 96822

Dr. Irwin Sarason
Department of Psychology
University of Washington
Seattle, WA 98195

Dr. Edgar H. Schein
Sloan School of Management
Massachusetts Institute of Technology
Cambridge, MA 02139

Dr. Saul B. Sells
Texas Christian University
Fort Worth, TX 76129

Dr. Siegfried Streufert
Department of Psychology
Purdue University
Lafayette, IN 47907

Dr. Richard E. Sykes
Minnesota Systems Research, Inc.
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7710 Old Springhouse Road
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School of Organization & Management
Yale University
56 Hillhouse Ave.
New Haven, CT 06520

Dr. Paul Wall
Div. of Behavioral Science Research
Tuskegee Institute
Tuskegee, AL 36088

Dr. Wilkenfeld
University of Maryland
College Park, MD 20742

Dr. Philip G. Zimbardo
Dept. of Psychology
Stanford University
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Mr. Richard T. Mowday
College of Business Administration
University of Nebraska, Lincoln
Lincoln, NB 68588

Eugene F. Stone
Assistant Professor of Management
Dept. of Administrative Sciences
Purdue University
West Lafayette, IN 47907

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Johannes M. Pennings
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Carnegie-Mellon University
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Dr. John A. Drexler, Jr.
Battelle Human Affairs Research
Center
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Seattle, WA 98105

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Graduate School of Management
Northwestern University
Evanston, IL 60201

Dr. Bill Curtis
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